

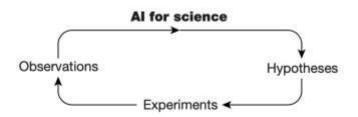


Outline

- Al for Science
- Multimodal Scientific Data
- Building Foundation Models for Science
 - ATLANTIC: Structure-Aware LLMs for Interdisciplinary Science
 - SCITUNE: Multimodal Agents for Scientific Reasoning
- Key Takeaways



Al for Science





Weather forecasting



Rare event selection in particle collisions

Deep learning forecasts impact of human missense variants Battery design pp. 1284 & 1303 Language modelling for optimization biomedical sequences Magnetic control of nuclear fusion reactors High-throughput virtual screening Planning chemical synthesis pathway Navigation in the hypothesis space Neural solvers of differential equations Super-resolution 3D Hydropower station live-cell imaging location planning Synthetic electronic Symbolic regression health record generation Wang, Hanchen, et al. "Scientific discovery in the age of artificial PNNL-SA-191857

A hidden figure in the story of blockbuster obesity drugs p. 1274

Fall picks to read, visit, watch, and play p.1278

Science

Global exposure to contamination from metal mines p.1345

\$15 22 SEPTEMBER 2023 science.org

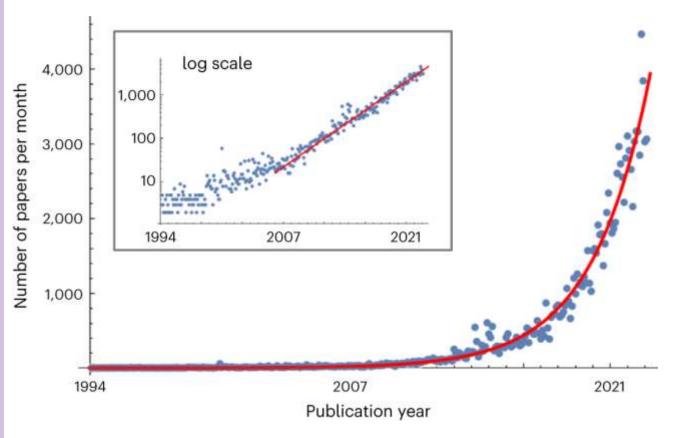
MAAAS

intelligence." Nature 620.7972 (2023): 47-60.

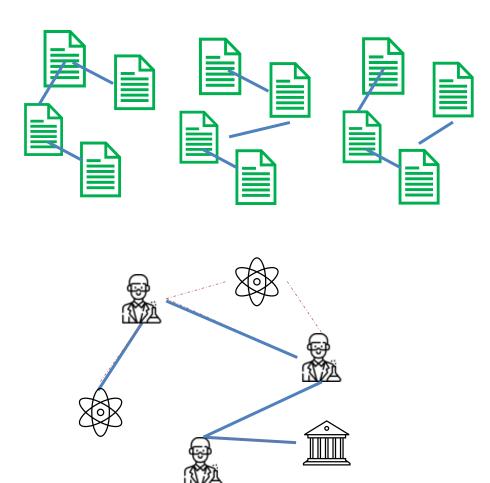


The Evolving Scientific Community

The doubling rate of papers per month is roughly 23 months.

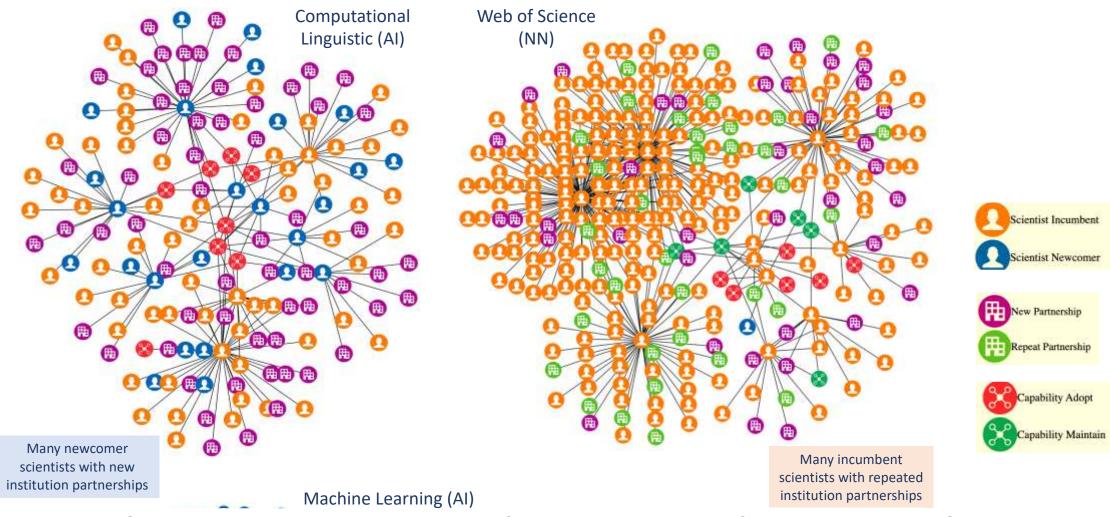


Krenn, M., Buffoni, L., Coutinho, B., Eppel, S., Foster, J. G., Gritsevskiy, A., ... & Kopp, M. (2023). Forecasting the future of artificial intelligence with machine learning-based link prediction in an exponentially growing knowledge network. Nature Machine Intelligence, 1-10.





The Evolving Scientific Community



Horawalavithana, Sameera, et al. "Anticipating Technical Expertise and Capability Evolution in Research Communities using Dynamic Graph Transformers." *arXiv preprint arXiv:2307.09665* (2023).

PNNL-SA-191857



Multimodal Scientific Data for Al Models

Tables



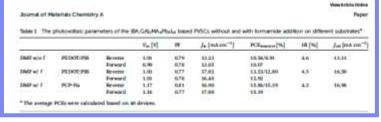
Text

SMILES

Images



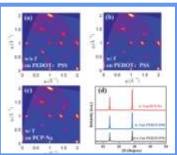
NC=C





Rg. 2 Cross-sectional SEM images of the IBA,GAEMA,Philip perox-Alte films without and with turnsmide addition on different

angle X-ray scattering (GFWAXS) posterns of (BA,GA),MA,Ph,Juperovskite films w/o and v formamide: ere recorded (Fig. 3a



Rg. 3 (a-c) 3D GMMAS patterns and 30 X-ray diffraction DND patients of the BIAGALHA, Pouls perchaite films without and will

#962 L.J. Alpert Clean A. 2019, 7, 18940-19965

posks can be detected. FWHM values of (111) and (502) peaks of the perceiving films narrow down from 0.216" and 0.212" (without formamide addition) to 0.200° and 0.222° (with firmumide addition), indicating the enlargement of grain size, which is in favor of improving carrier transport and suppressing charge recombination. ***

The effect on the carster lifetime of the (8A/JA),MA,Pb,1, perceskite films deposited from DMF with and without formamide on quarts substrates was evaluated through .oneresolved PL decay spectra (TRPL), as shown in ... q. 4a. The corresponding calculated results are supported in Table 91. † The TRFL curve was firted with a be apprecial decay function, and b). The Bragg w is the percentite film w/o f span $f(r) = A_r \exp^{-2r_r} + A_r \exp^{-2r_r}$ containing a fast decay and a slow a slightly wider por angle than the film w/f, indicating that the Heroy promus," The PL atetims, calculated by the formula of formamide a^{*} ion improves the growth orientation of the $t_{ant} = t_{1} \times frac_{t_{1}} + t_{2} \times frac_{t_{2}} = A_{c}t_{1}/(A_{c}t_{1} + A_{c}t_{2})$, thus, $a = t_{1} \times frac_{t_{1}} + t_{2} \times frac_{t_{2}} = A_{c}t_{1}/(A_{c}t_{1} + A_{c}t_{2})$, thus, tryonals is the percession film. The corresponding Xeay 1 - frac_{s,1} is prolonged from 1.20 ns to 6.17 ns because of diffus on (XRD) patterns and parameters are presented in formamide addition, indicating an improved film quality with Pl of and Table 2. The diffraction peaks at 14.1" and 28.3" can liver trup status for the BA,MA,Pb,L... film based on the DMB! or attributed to the (111) and (202) lattice planes of the proce- formantide reletion. Fig. 4b shows that V_{ec} varies logarithms. sine time, respectively 24144 For the film with 3% immunide cally (In/E) as a function of light intensity with a slope of 1.3487 addition, the intensity enhancement of the [111] and (202) 4, 1.0527/s for films based on DMF without and with formamide, respectively, indicating a formamide addition induced reduction in monomolecular recombination." To further investigate the decreas transtate density of nercoskite films with and without formunide addition, the electron-only devices (PIO/SeO₂/perovskite/PC₄,BM/BCP/Ag) are fabricated. Corresponding J-V curves are shown in Fig. 86.1 The details about the calculation of trap density are given in the ESF1 based on the literature, was When formamide was added, the value of Vyes, (0.77 V) is smaller than that of the film without formamide addition (9.88 V), indicating that formunide addition can reduce electron trap-state density. This reduction correlates well with the observations of increased grain size, crystallinity and

> Table 3 XRD pettern parameters of the BIA, GAL, MA, Pb., L., per outside ims without and with formerside addition on different substrates.

		Pfame	(10:1)	(1001)
670	DMF wis fast PEDCEPS.	FWIOM [1]	6.216	929
		Inometry (cpd	4.4×10^4	$4.8 \times 10^{\circ}$
	DMF w/ f on PEDOT:PSS	PWHM [4.309	6,223
DI-		Internity [cps]	0.0×10^4	7.7×10^4
m	Ethil will on PCP-No.	FWHM [1]	0.316	8.317
		Instruits lopel	6.0×10^{4}	9.9×10^{9}

Podiminary code for downloading and using the small model m available at https://github.com/cpensi/spt-I

Equations



Notes and references

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- 5 S. Ahmad, F. Fo, S. Yo, Q. Yang, X. Liu, X. Wang, X. Wang, X. Gno and C. H, Joak, 2019, 3, 794-806.
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- N. Zhou, Y. Shen, L. Li, S. Turr, N. Liu, G. Zheng, Q. Chen and H. Zhou, J. Am. Chan. Soc., 2016, 146, 433-465.
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Citation Graphs



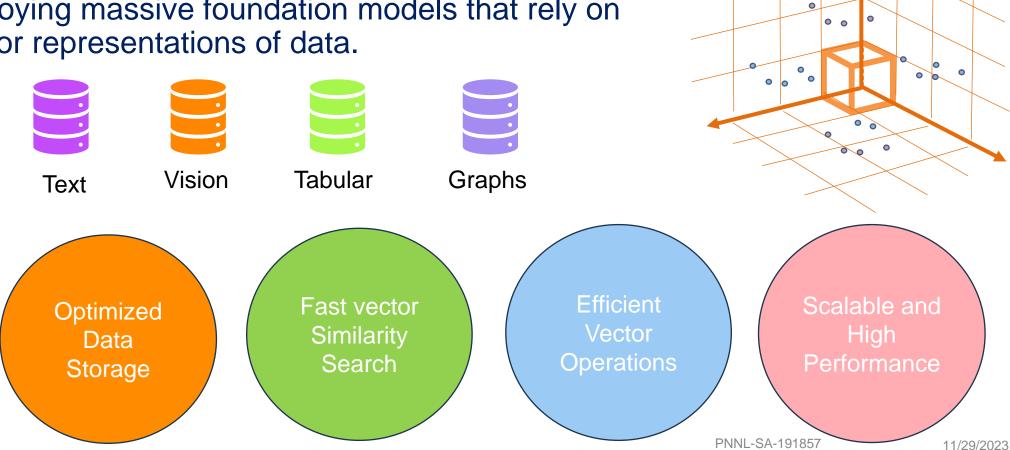
Code





Multimodal Scientific Data with Vector Databases

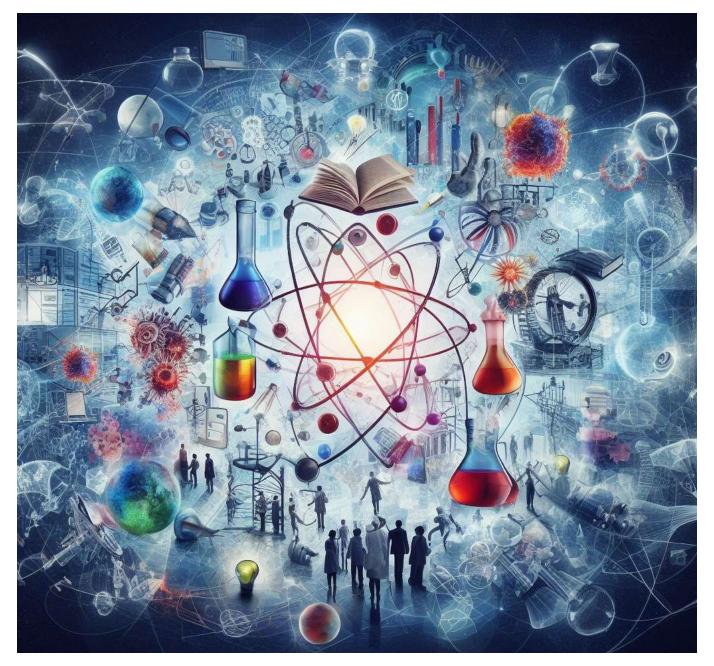
Al-ready vector databases provide the scalable vector storage and retrieval essential for developing and deploying massive foundation models that rely on vector representations of data.





ATLANTIC: Structure-Aware LLMs for Interdisciplinary Science

Developing LLMs to reason across multiple scientific disciplines





Cross-Disciplinarity Scientific Reasoning

Develop an integrated strategy to improve solar technology, drive down costs, model environmental benefits, and ensure inclusive deployment of solar energy across societies.



investigating novel materials that can absorb and convert sunlight into electricity at higher efficiencies



synthesizing and testing different compounds to find ones optimal for photon absorption.



designing nanoscale architectures for solar cells to minimize electron-hole recombination losses.



modeling how increased adoption of solar energy could reduce greenhouse gas emissions from electricity production over time.

Climate Scientist



analyzing solar policies and incentives to understand how to further drive down costs and encourage widespread adoption.

Economist



studying how solar energy can be equitably distributed so all communities have access to clean electricity.

OCIOIOGIST PNNL-SA-191857 11/29/2023



Cross-Document Scientific Reasoning

What is the name of the nuclear fuel used in the reactor?

Uranium Oxide (UO2)

Uranium oxide (UO2) is important from the technological point of view as a nuclear fuel. It has also been a challenging material for electronic structure calculations. On the one hand, being a nuclear fuel, understanding of thermal properties such as specific heat, thermal expansion and thermal conductivity in terms of structure at the atomistic/electronic scale is of great interest. On the other hand, complexity of the electronic structure makes material description very challenging. In the context of calculating material properties from the first principles, UO2 has proven to be a non-trivial material. Conventional density functional theory (DFT) with local density approximation (LDA) and/or generalized gradient approximation (GGA), which has been quite successful in predicting the ground state structure and properties of a wide range of materials, has failed to give the proper description of UO2.

Intra-Document Reasoning

Which country collaborated in the development of Fast Breeder Test reactor at the Indira Gandhi Center for Atomic Research?

Fast breeder reactors constitute the second stage of India's three-stage nuclear energy programme, for effective utilization of the country's limited reserves of natural uranium and exploitation of its large reserves of thorium. The Reactor Research Centre (renamed Indira Gandhi Centre for Atomic Research in 1985) was established at Kalpakkam, 80 km south of Madras (now Chennai), in 1971, with the mission to develop the technology of sodium cooled fast reactors.

Similar Topic Fast Breeder Reactor

At the heart of the Reactor Research Centre was proposed a sodium cooled test reactor, named Fast Breeder Test Reactor, which would serve as a test bed for irradiation of fuels and materials and provide experience in large scale sodium handling and reactor operation. An agreement was signed with CEA (France) for transfer of the design of the Rapsodie reactor, training of personnel in Rapsodie and transfer of manufacturing technology of critical components.

Automated Reasoning Steps

France

The Reactor Research Centre is renamed to Indira Gandhi Center for Atomic Research

The Reactor Research Centre developed Fast Breeder Reactor

Fast Breeder Reactor is based on Rapsodie Reactor

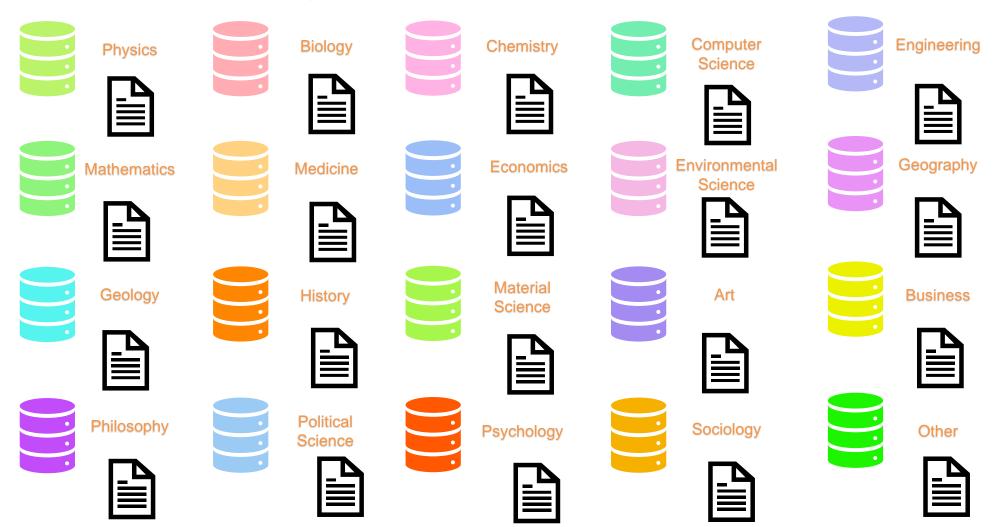
Rapsodie Reactor is deployed at The French Alternative Energies and Atomic Energy Commission or CEA

CEA is in France



Interdisciplinary Scientific Datasets

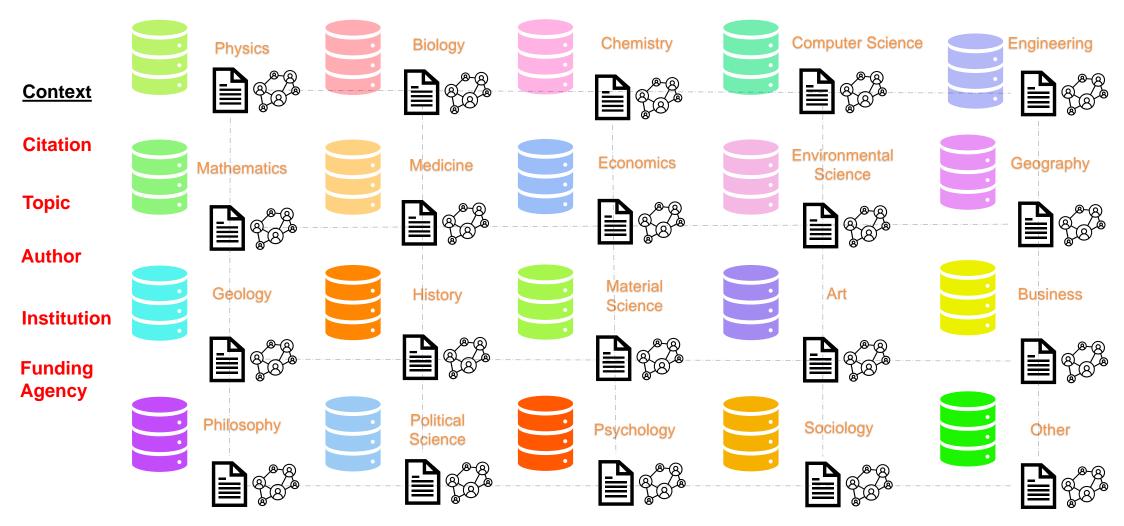
Content (Text) Representations





Interdisciplinary Scientific Datasets

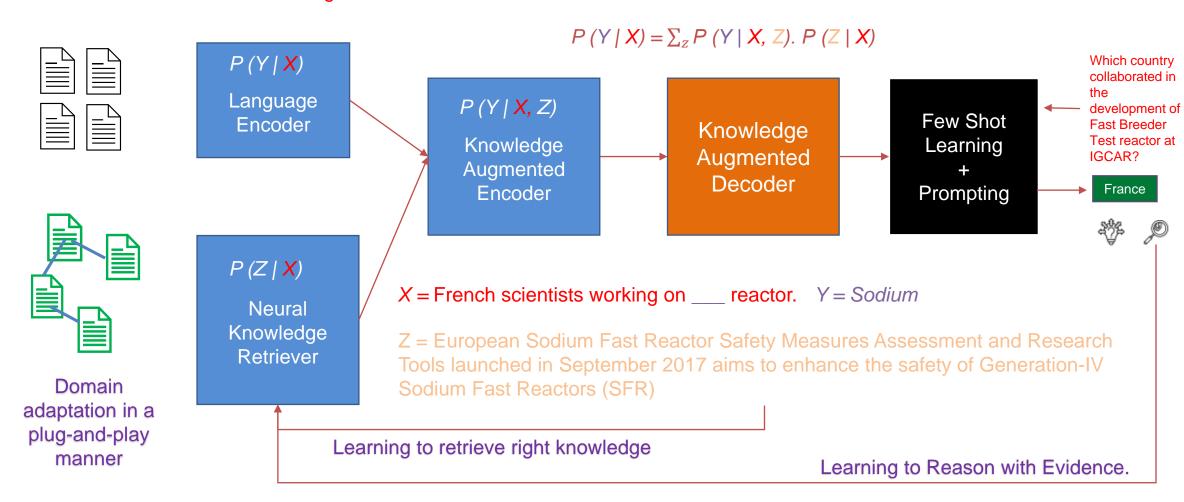
Content (Text) + Context (Graph) Representations





ATLANTIC Model Architecture

X = French scientists working on ____ reactor. Y = Sodium



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ATLANTIC Model Performance

Scientific Evidence Generation

How useful are the evidences generated from structural aware LLMs to justify model predictions in science tasks?

Atlas

"# Below is an input containing a title-abstract pair. Classify this input into one or more possible Field of Study categories ['..']

Input: ## Title: Characterization of N-Glycosylation Status of Micro-level Glycoprotein Using Solid Phase Extraction Based Techniques.

Abstract: A new strategy integrating the latest hydrophilic interaction chromatographic(HILIC) method with mass spectrometry technologies was developed for the enrichment and determination of intact glycopeptides and glycan structures from a glycoprotein. The average molecular weight, the ratio of glycosylation, the glycosite and the structures of glycoforms of ribonuclease B(RNaseB) were determined by MALDI-TOF-MS and ESI-LTQ-FT-MS.RNaseB contains 8.43% glycan and has a single glycosylation site at Asn34 with the glycan structure varied from five to nine mannose residues(Man5-9GicNAc2). The strategy paves the way for systematic and confident analysis of complex glycoproteins with important biological or pharmaceutical functions.

Response: Chemistry

Evidence traces:

Passage 1: [Geology] Title: Paleomagnetic reversals in Miocene dikes, and tectonic evolution of the Crossman block, Mohave Mountains, Arizona

Passage 2: [Social Science] Title: Q&A with Photographer Paul Vecsei

Atlantic

"# Below is an input containing a title-abstract pair. Classify this input into one or more possible Field of Study categories [".."]

Input: ## Characterization of N-Glycosylation Status of Microlevel Glycoprotein Using Solid Phase Extraction Based
Techniques ## Abstract: A new strategy integrating the latest
hydrophilic interaction chromatographic(HILIC) method with
mass spectrometry technologies was developed for the
enrichment and determination of intact glycopeptides and glycan
structures from a glycoprotein. The average molecular weight, the
ratio of glycosylation, the glycosite and the structures of
glycoforms of ribonuclease B(RNaseB) were determined by
MALDI-TOF-MS and ESI-LTQ-FT-MS.RNaseB contains 8.43%
glycan and has a single glycosylation site at Asn34 with the
glycan structure varied from five to nine mannose
residues(Man5-9GlcNAc2). The strategy paves the way for
systematic and confident analysis of complex glycoproteins with
important biological or pharmaceutical functions.

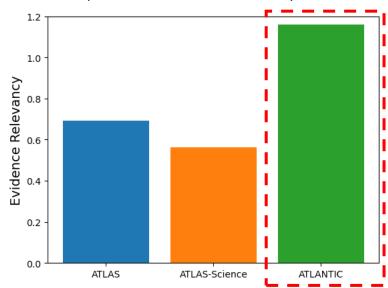
Response: Chemistry

Evidence traces:

Passage 1: [Chemistry/Biology] Title: Aryl hydrocarbon receptor in combination with Stat1 regulates LPS-induced inflammatory responses

Passage 2: [Chemistry/Biology] Title: Osteogenic protein-1 attenuates the inflammatory cytokine-induced NP cell senescence through regulating the ROS/NF-kB pathway.

Intra-disciplinary Scientific Reasoning (Document Classification)



Structure aware LLMs retrieve relevant passages to justify model predictions better than text-only models

The query relevance metric calculates the semantic similarity of the extracted passages with the input query via their embeddings. Similarity scores are obtained via the dot product of the embeddings.



ATLANTIC Model Performance

Scientific Evidence Generation

How useful are the evidences generated from structural aware LLMs to justify model predictions in science tasks?

Atlas

"# question: Which of the following is the most likely benefit of periodic natural wildfires in some forest ecosystems? options:

(A) The fires remove dead and decaying plant matter, reducing the risk of more intense and destructive fires. (B) The fires leach nutrients from the soil, preventing the germination of plants that might compete with native species. (C) The fires drive off herbivores whose plant-based diets reduce the amount of vegetation. (D) The fires dry out the soil and decrease the chance of flooding after heavy rains.

Response: A

Evidence traces:

Passage 1: [Art, History] Title: THE 'LAST BOLSHEVIK' -MARKER.C

Passage 2: [Maths, Engineering] Title: C Frame Transformations

Atlas

"# question: The Minoan economy may have been especially vulnerable to natural catastrophe because it relied heavily on : options: (A) agriculture (B) maritime trade (C) metalworking (D) slave labor answer

Response: B

Evidence traces:

Passage 1: [Computer science] Title: B Unicode Representation

Passage 2: [Maths, Engineering] Title: C Frame Transformations

Atlantic

"# question: Which of the following is the most likely benefit of periodic natural wildfires in some forest ecosystems? options:

(A) The fires remove dead and decaying plant matter, reducing the risk of more intense and destructive fires. (B) The fires leach nutrients from the soil, preventing the germination of plants that might compete with native species. (C) The fires drive off herbivores whose plant-based diets reduce the amount of vegetation. (D) The fires dry out the soil and decrease the chance of flooding after heavy rains.

Response: A

Evidence traces:

Passage 1: [Geology] Title: Another Threat to Borneo's Rainforests?

Passage 2: [Geology] Title: The potential of secondary forests

Atlantic

"# question: The Minoan economy may have been especially vulnerable to natural catastrophe because it relied heavily on: options: (A) agriculture (B) maritime trade (C) metalworking (D) slave labor answer

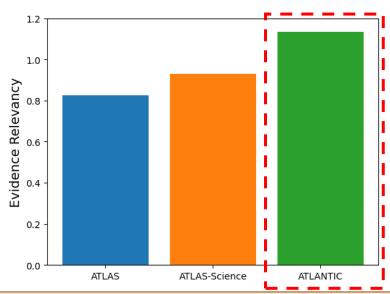
Response: B

Evidence traces:

Passage 1: [Economics] Title: Public debt and endogenous growth

Passage 2: [Economics] Title: Land and rent

Inter-disciplinary Scientific Reasoning (Science Question and Answering)



Structure aware LLMs retrieve relevant passages to justify model predictions better than text-only models

The query relevance metric calculates the semantic similarity of the extracted passages with the input query via their embeddings. Similarity scores are obtained via the dot product of the embeddings.



ATLANTIC Model Performance

Faithfulness (Accuracy + Evidence Generation)

Does retrieving structural knowledge help to improve the overall model performance?



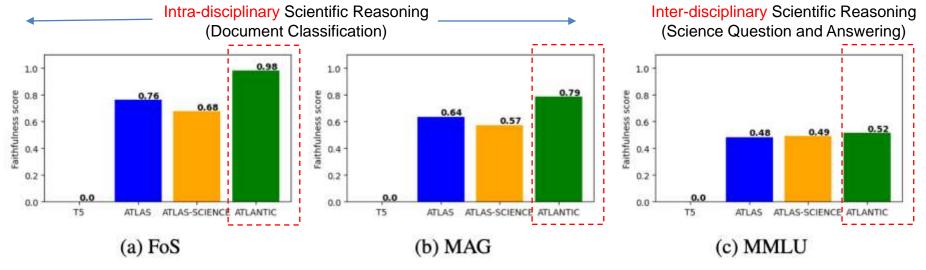


Figure 2: Faithfulness scores across FOS, MAG and MMLU benchmarks. Faithfulness score is the harmonic mean between the accuracy and relevance of the retrieved passages, which gives a holistic view on the trustworthiness of the model.

Faithfulness score is a measure combining generation accuracy and relevance score of the retrieved passages.

T5, ATLAS, and ATLAS-Science are baseline models trained only with textual knowledge.

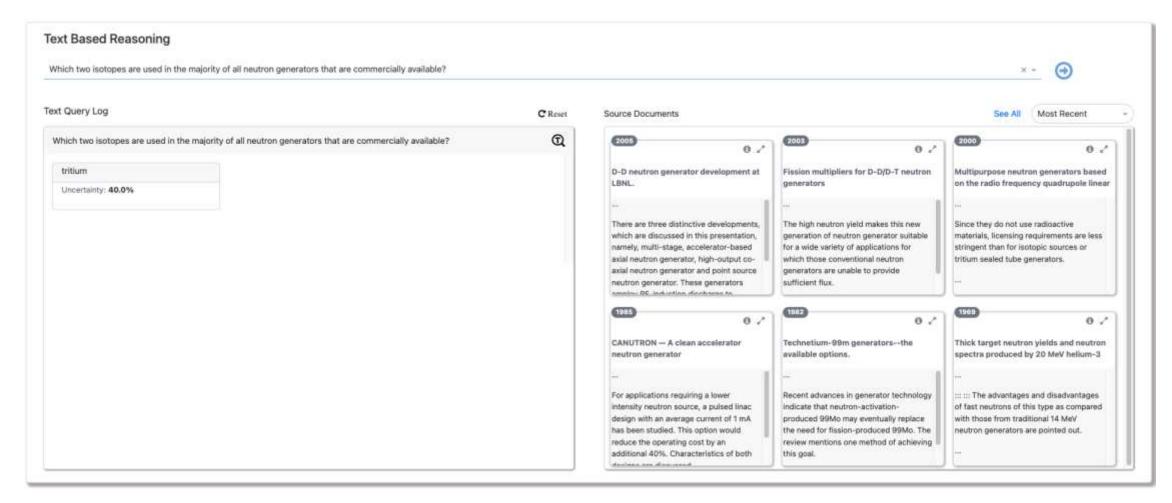
T5 does not generate evidence such that the faithfulness score is zero.

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ATLANTIC Model Demo

Human-Al Teaming

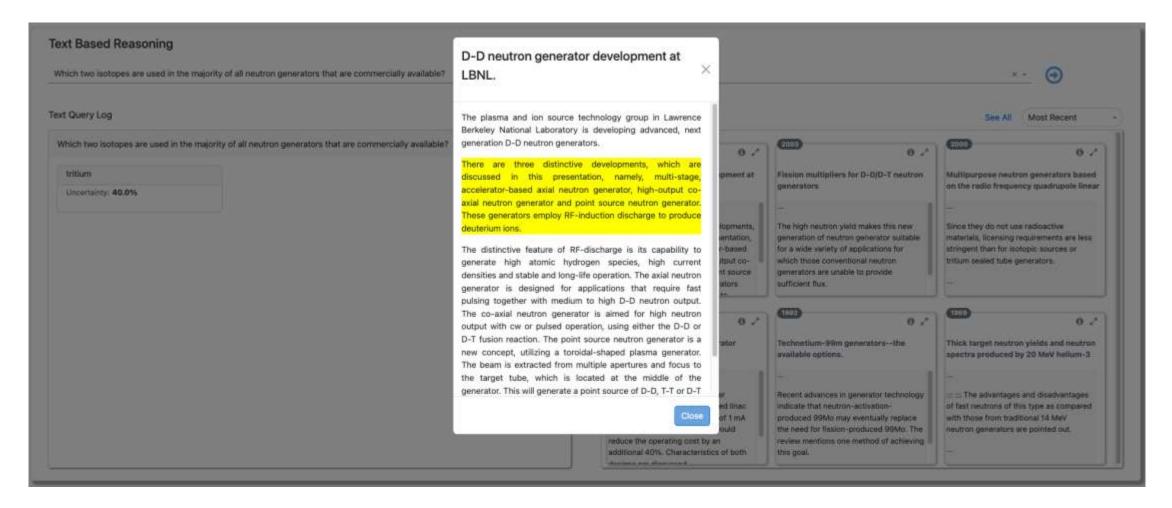


EXPERT 2.0 Human-Al Scientific Reasoning Engine https://github.com/pnnl/EXPERT2



ATLANTIC Model Demo

Human-Al Teaming



EXPERT 2.0 Human-Al Scientific Reasoning Engine https://github.com/pnnl/EXPERT2



SciTune: Multimodal Agents for Scientific Reasoning

"A llama in a science lab coat"

Developing multimodal agents to reason across multiple scientific disciplines





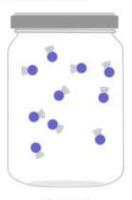
Scientific Multimodal Reasoning

Question

Compare the average kinetic energies of the particles in each sample. Which sample has the higher temperature?

Context

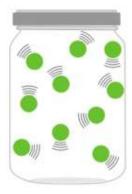
The diagrams below show two pure samples of gas in identical closed, rigid containers. Each colored ball represents one gas particle. Both samples have the same number of particles.



Sample A

Mass of each particle: 32 u

Average particle speed: 1,000 m/s



Sample B

Mass of each particle: 40 u

Average particle speed: 1,000 m/s

Choices

sample A

sample B

neither; the samples have the same temperature

Which of the following could Kathleen's test show?

Context

Question

People can use the engineering-design process to develop solutions to problems. One step in the process is testing if a potential solution meets the requirements of the design. The passage below describes how the engineering-design process was used to test a solution to a problem. Read the passage. Then answer the question below. People with diabetes sometimes take a medicine made from insulin. Insulin can be made by a special type of bacteria. Kathleen was a bioengineer who wanted to increase the amount of insulin that the bacteria produced by 20%. She read that giving the bacteria more nutrients could affect the amount of insulin they produced. So, Kathleen gave extra nutrients to some of the bacteria. Then, she measured how much insulin those bacteria produced compared to bacteria that did not get extra nutrients. Figure: studying bacteria in a laboratory.



Choices

whether she added enough nutrients to help the bacteria produce 20% more insulin

whether producing more insulin would help the bacteria grow faster

whether different types of bacteria would need different nutrients to produce insulin

Physics Example

Science and Eng. Practices Example



Interdisciplinary Scientific Datasets

Multimodal Content (Text + Images) Representations











Chemistry







Engineering









Medicine



Economics



Environmental Science



Geography





Geology



History



Material Science







Business





















Philosophy



Political Science



Psychology



Sociology























SciTune Multistage Concept and Task Alignment

(+)

How to make an LLM that can see and reason in the scientific multimodal world?

How to chain vision experts with LLMs?

How to learn scientific image representations?

How to generate visual instructions?

Which human-generated scientific data modalities support to align LLMs with scientific concepts?

How to perform scientific multimodal reasoning with visual grounded QA and text-driven explanations?

How to evaluate the scientific multimodal reasoning?

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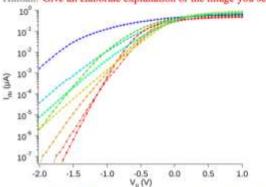


SciTune Multimodal Token Generation

SciTune Multimodal Instruction Examples. We distinguish the system message s₀, natural language instruction s₁, scientific figure type s₁, caption s₂, OCR s₃ and paragraph mentions s₃.

A chat between a curious human and an artificial intelligence assistant. The assistant gives helpful, detailed, and polite answers to the human's questions.

Human: Give an elaborate explanation of the image you see.

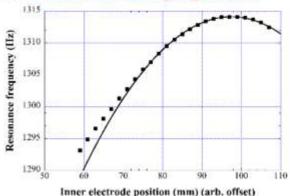


Assistant: Graph Plot Room temperature characteristics (drain-source current versus gate voltage) for a set of nominally identical samples from the same wafer. Sample to sample variations are very important, especially below the threshold voltage (-0.5 V for the best device, in red). In the most extreme case (blue curve) the many decades of excess current compared to the best device are attributed to direct transport through individual arsenic dopants which have diffused into the channel after doping and annealing steps.

The source-drain voltage is 10mV for these data.

FIG. 6: figure S1: Room temperature characteristics (drain-source current versus gate voltage) for a set of nominally identical samples from the same wafer. A chat between a curious human and an artificial intelligence assistant. The assistant gives helpful, detailed, and polite answers to the human's questions.

Human: Describe the following image in detail.



Assistant: Graph Plot Resonance frequency of the (1, 0) mode of the r1 = 4 cm cavity filled with 1 atm of N2 as a function of the vertical position of the central electrode.

Inner electrode position, (arb, offset)

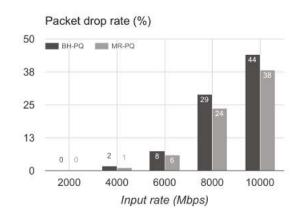
In Fig. 10 we have an example of this behavior: the resonance frequency shows a maximum which corresponds to a minimum in the eccentricity of the electrode [39].

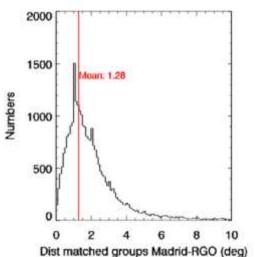
$$p(x) = \prod_{j=1}^{n} p(s_{T>j}|s_{V}, s_{I}, s_{T< j})$$

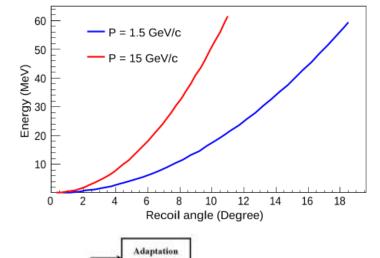


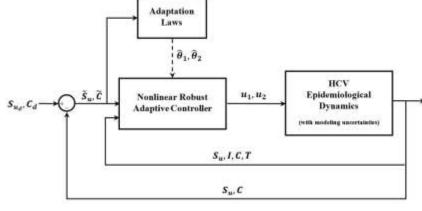
Scientific Image Captioning

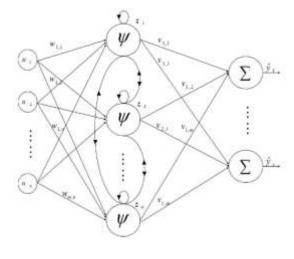
Testing the Scientific Concept Alignment Stage Pretraining

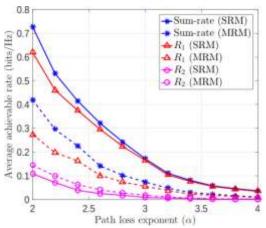












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Scientific Image Captioning

Table 8: A Sample of Generated Captions. We highlight the gold standard caption in red, and generated captions from the BLIP (Li et al., 2022) model in gray. LLaMA-SciTune model first generates the figure types followed with the captions colored in blue.



Packet drop rate

a chart of a bar chart with a number of different items

Bar Chart Packet drop rate for each method,



The kinetic energy of the recoil protons as a function of the recoil angle at beam momenta P=1.5 and 15 GeV/c, blue and red, respectively.

a plot of a curve with a blue line and a red line.

Graph Plot The angular distribution of the electron recoil spectrum in the 1.5 GeV/c and 15 GeV/c electron beams.



Artificial neural network structure.

a diagram of a network with several different paths.

Node Diagram The generative neural network.



ROC curves of cIBP-VAE in comparison to alternative models on the clinical ECG data set.

a plot of the average and average time of a cell phone.

Graph Plot ROC curves of c-VAE, CNN, and c-VAE+CNN on the cerebellar atrophy dataset,



Functional architecture of the developed prototype.

a diagram of a camera and a person on a phone.

Node Diagram An overview of the system architecture of the proposed method.

Distance between matched groups in Madrid and RGO catalogs (bins of 0.1 degrees). The red line represents the mean value, a plot of a line of data with a red line and a white line.

Graph Plot Distance correlation between groups matched by Madrid RGO.



Comparison of penetration rate of mobile broadband subscribers with that of fixed broadband subscribers.

a chart of the number of people who are using the internet.

Bar Chart The average rate of mobile broadband subcribers and fixed broadband subscribers for each quarter (in thousands). Table 1: Accuracy of Generating the Figure Types. We also report the zero-shot figure type classification performance of the CLIP (Radford et al., 2021) model.

Figure Type	CLIP	LLaMA-SciTune
Graph Plot	54.07	93.48
Scatterplot	53.48	79.06
Node Diagram	91.02	98.71
Equation	65.71	94.28
Bar Chart	28.94	84.21
All	58.68	92.42

Table 2: Evaluation of Generated Figure Captions

Model	BLEU	ROUGE
BLIP (Li et al., 2022)	0.02 ± 0.02	0.10 ± 0.07
LLaMA-SciTune	0.05±0.03	0.13±0.08



ScienceQA Multimodal Reasoning

3 subject areas, 26 topics, 127 categories, and 379 skills

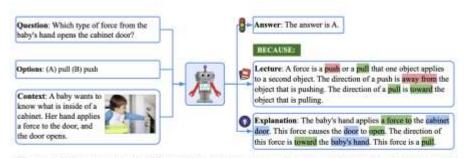
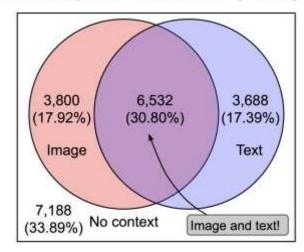


Figure 1: We construct the SCIENCEQA dataset where a data example consists of multimodal question answering information and the grounded lecture and explanation. We study if QA models can generate a reasonable explanation to reveal the chain-of-thought reasoning.



Statistic	Number		
Total questions	21,208		
Questions with text context	10,220 (48.2%)		
Questions with image context	10,332 (48.7%)		
* Image of natural format	≈2,960 (14.0%)		
* Image of diagram format	≈7,372 (34.8%)		
Questions with both contexts	6,532 (30.8%)		
Questions without any context	7,188 (33.9%)		
Questions with a lecture	17,798 (83.9%)		
Questions with a explanation	19,202 (90.5%)		
Different questions	9,122		
Different lectures	261		
Topic classes	26		
Category classes	127		
Skill classes	379		
Average question length	12.11		
Average choice length	4.40		
Average lecture length	125.06		
Average explanation length	47.66		

Table 1: Main statistics in SCIENCEQA.

Grades	Number	Percent
Grade 1	95	0.45%
Grade 2	1,678	7.91%
Grade 3	3,032	14.3%
Grade 4	3,544	16.71%
Grade 5	3,086	14.55%
Grade 6	2,450	11.55%
Grade 7	2,749	12.96%
Grade 8	2,546	12.0%
Grade 9	491	2.32%
Grade 10	558	2.63%
Grade 11	539	2.54%
Grade 12	440	2.07%

(a) Grade distribution statistics.

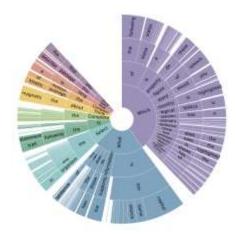


Figure 2: Question distribution in SCIENCEQA.



(b) Grade distribution visualization.

ScienceQA is the SOTA Science-Focused Multimodal Reasoning Benchmark



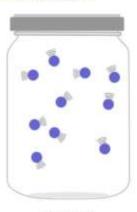
Natural Sciences - Physics

Question

Compare the average kinetic energies of the particles in each sample. Which sample has the higher temperature?

Context

The diagrams below show two pure samples of gas in identical closed, rigid containers. Each colored ball represents one gas particle. Both samples have the same number of particles.



Sample A

Mass of each particle: 32 u

Average particle speed: 1,000 m/s



Sample B

Mass of each particle: 40 u

Average particle speed: 1,000 m/s

Choices

sample A

sample B

neither; the samples have the same temperature

PNNL-SA-191857

Answer

sample B

Lecture

The temperature of a substance depends on the average kinetic energy of the particles in the substance. The higher the average kinetic energy of the particles, the higher the temperature of the substance. The kinetic energy of a particle is determined by its mass and speed. For a pure substance, the greater the mass of each particle in the substance and the higher the average speed of the particles, the higher their average kinetic energy.

Solution

The particles in both samples have the same average speed, but each particle in sample B has more mass than each particle in sample A. So, the particles in sample B have a higher average kinetic energy than the particles in sample A. Because the particles in sample B have the higher average kinetic energy, sample B must have the higher temperature.

Prediction

Assistant: LECTURE: The temperature of a substance depends on the average kinetic energy of the particles in the substance. The higher the average kinetic energy of the particles, the higher the temperature of the substance. The kinetic energy of a particle is determined by its mass and speed. For a pure substance, the greater the mass of each particle in the substance and the higher the average speed of the particles, the higher their average kinetic energy. SOLUTION: The particles in both samples have the same average speed, but each particle in sample B has more mass than each particle in sample A. So, the particles in sample B have a higher average kinetic energy than the particles in sample A. Because the particles in sample B have the higher average kinetic energy, sample B must have the higher temperature. The answer is B.

Accuracy Label

correct



Natural Sciences – Science and Eng. Practices

Question

Which of the following could Kathleen's test show?

Context

People can use the engineering-design process to develop solutions to problems. One step in the process is testing if a potential solution meets the requirements of the design. The passage below describes how the engineering-design process was used to test a solution to a problem. Read the passage. Then answer the question below. People with diabetes sometimes take a medicine made from insulin. Insulin can be made by a special type of bacteria. Kathleen was a bioengineer who wanted to increase the amount of insulin that the bacteria produced by 20%. She read that giving the bacteria more nutrients could affect the amount of insulin they produced. So, Kathleen gave extra nutrients to some of the bacteria. Then, she measured how much insulin those bacteria produced compared to bacteria that did not get extra nutrients. Figure: studying bacteria in a laboratory.



Choices

whether she added enough nutrients to help the bacteria produce 20% more insulin

whether producing more insulin would help the bacteria grow faster

whether different types of bacteria would need different nutrients to produce insulin

Answer

whether she added enough nutrients to help the bacteria produce 20% more insulin

Lecture

People can use the engineering-design process to develop solutions to problems. One step in the process is testing if a potential solution meets the requirements of the design. How can you determine what a test can show? You need to figure out what was tested and what was measured. Imagine an engineer needs to design a bridge for a windy location. She wants to make sure the bridge will not move too much in high wind. So, she builds a smaller prototype, or model, of a bridge. Then, she exposes the prototype to high winds and measures how much the bridge moves. First, identify what was tested. A test can examine one design, or it may compare multiple prototypes to each other. In the test described above, the engineer tested a prototype of a bridge in high wind. Then, identify what the test measured. One of the criteria for the bridge was that it not move too much in high winds. The test measured how much the prototype bridge moved. Tests can show how well one or more designs meet the criteria. The test described above can show whether the bridge would move too much in high winds.

Solution

rediction

Assistant: LECTURE: People can use the engineering-design process to develop solutions to problems. One step in the process is testing if a potential solution meets the requirements of the design. How can you determine what a test can show? You need to figure out what was tested and what was measured. Imagine an engineer needs to design a bridge for a windy location. She wants to make sure the bridge will not move too much in high wind. So, she builds a smaller prototype, or model, of a bridge. Then, she exposes the prototype to high winds and measures how much the bridge moves. First, identify what was tested. A test can examine one design, or it may compare multiple prototypes to each other. In the test described above, the engineer tested a prototype of a bridge in high wind. Then, identify what the test measured. One of the criteria for the bridge was that it not move too much in high winds. The test measured how much the prototype bridge moved.

Tests can show how well one or more designs meet the criteria. The test described above can show whether the bridge would move too much in high winds. The answer is A.

Accuracy Label



ScienceQA Performance (Accuracy)

LLaMA-SciTune (13B) model outperforms the human performance on average.

LLaMA-SciTune models pretrained with additional scientific modalities such as caption, figure type, OCR, and figure mentions perform better than the model pretrained only with captions.

There is a significant performance advantage of the models trained with larger language decoder model (13B) compared to the relatively smaller model (7B).

Table 3: Results (accuracy %) on ScienceQA dataset. Question classes: NAT = natural science, SOC = social science, LAN = language science, TXT = text context, IMG = image context, NO = no context, G1-6 = grades 1-6, G7-12 = grades 7-12. We present two variants, *LLaMA-SciTune* (*C*) and *LLaMA-SciTune* (*CTOM*). Acronyms inside the parenthesis represent the input modalities used in the SciTune instruction template. E.g., Caption, Figure Type, OCR, and Figure Mentions. We use the notation ♠ to denote the models finetuned with GPT-3.5/4 synthetic instructions, or use GPT-3.5/4 for any support during the inference time. We bold the accuracy values that are greater than what humans achieved. For additional baseline results, please refer the public ScienceQA leaderboard²

Method	#Params	Avg	NAT	SOC	LAN	TXT	IMG	NO	G1-6	G7-12
Random Chance	-	39.83	40.28	46.13	29.25	47.45	40.08	33.66	39.35	40.67
Human Average		88.40	90.23	84.97	87.48	89.60	87.50	88.10	91.59	82.42
UnifiedQA	223M	70.12	68.16	69.18	74.91	63.78	61.38	77.84	72.98	65.00
UnifiedQA (CoT)	223M	74.11	71.00	76.04	78.91	66.42	66.53	81.81	77.06	68.82
♠ GPT-3 (Zero Shot)	175B	74.04	75.04	66.59	78.00	74.24	65.74	79.58	76.36	69.87
♠ GPT-3 (CoT) (ALE)	175B	75.17	75.44	70.87	78.09	74.68	67.43	79.93	78.23	69.68
♠ ChatGPT CoT	175B+	78.31	78.82	70.98	83.18	77.37	67.92	86.13	80.72	74.03
♠ GPT-4 CoT	1T+	83.99	85.48	72.44	90.27	82.65	71.49	92.89	86.66	79.04
Multimodal-CoT	223M	84.91	87.52	77.17	85.82	87.88	82.90	86.83	84.65	85.37
Multimodal-CoT	770M	91.68	95.91	82.00	90.82	95.26	88.80	92.89	92.44	90.31
♠ LLaMA-Adapter	13B	85.19	84.37	88.30	84.36	83.72	80.32	86.90	85.83	84.05
♠ LLaVa	13B	90.92	90.36	95.95	88.00	89.49	88.00	90.66	90.93	90.90
♠ LLaVa + GPT-4 (judge)	13B	92.53	91.56	96.74	91.09	90.62	88.99	93.52	92.73	92.16
♠ Chameleon (ChatGPT)	175B+	79.93	81.62	70.64	84.00	79.77	70.80	86.62	81.86	76.53
♠ Chameleon (GPT-4)	1T+	86.54	89.83	74.13	89.82	88.27	77.64	92.13	88.03	83.72
LLaMA-SciTune (C)	7B	85.61	84.36	92.23	82.81	89.56	81.26	88.29	81.28	86.03
LLaMA-SciTune (CTOM)	7B	86.11	84.50	94.15	82.91	88.35	83.64	88.74	85.05	85.60
LLaMA-SciTune (CTOM)	13B	90.03	89.30	95.61	87.00	93.08	86.67	91.75	84.37	91.30



ScienceQA Performance (Evidence)

Did the model accurately explain the reasoning that supports the answer?

Table 4: Few-shot performance analysis. We report the number of times lectures seen during the training in frequency, and the number of test questions with the lecture.

Frequency	#Questions	Accuracy (7B)	Accuracy (13B)
5	36	75.00	83.33
10	125	81.60	85.60
25	412	80.34	85.92
50	1140	81.05	86.14

The model generates the answer more accurately when it acquires the relevant background knowledge during training

Table 5: Evaluation of generated lectures and solutions.

	7B Mod	lel	13B Mo	odel
	BLEU	ROUGE	BLEU	ROUGE
All answ	ers	7		
Lecture	0.763	0.778	0.854	0.868
Solution	0.791	0.838	0.872	0.921
Correct a	answers			
Lecture	0.765	0.780	0.847	0.861
Solution	0.829	0.873	0.893	0.937
Incorrec	t answer	S		
Lecture	0.751	0.767	0.909	0.924
Solution	0.565	0.631	0.694	0.778

The model generates the solution text with higher accuracy than the lecture text.



Key Takeaways

Advancing Interdisciplinary Science with Foundation Models

Synthesize

Adoption

Scalability

Accessibility

Synthesis of knowledge from diverse scientific disciplines

Rapidly adapt to new tasks with minimal labeled data

Learning complex concepts spanning disciplinary boundaries from massive datasets.

Higher level analysis, hypothesis development and knowledge integration across disciplines

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Foundation Models for Science Papers

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